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Research Article

A Novel Design of Hybrid Precoder in Multicell, Multiuser Heterogeneous Network

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In this paper, the precoders capable of maximizing the weighted sum rate (WSR) for multicell scenarios under power budget constraint conditions per cell were considered based on the MIMO system performance. This rate is strongly affected by intracellular interference, so we recommend using coordinated beam forming (CBF). If the number of user equipment provided per cell is small enough to the number of transmit antennas, simple linear beamformers, such as matched filter (MF), achieve higher performance rates. In general cases, two algorithms meet the best performance in terms of the total achievable rate; these are KG (Kim Giannakis) and WSMSE (Weighted Sum Minimum Squared Error) algorithms. In the KG method, the objective function of the sum rate is suggested to be divided into two functions, one function for the desired user rate and the other for the sum rate of the remaining users. In the WSMSE algorithm, maximizing the sum rate is solved by redefining it as the problem of minimizing the MSE (Mean Square Error) function. These functions are convex and nonconvex functions, respectively. In the proposed method, the WSMSEs were modified to reduce the complexity and calculations to provide optimal performance in beamforming.

1. Introduction

Using the MIMO systems has some advantages as they use dozens of terminals that can provide services to many users simultaneously and therefore increase the spectral efficiency (SE) [1–7]. On the other hand, as the number of users in cellular networks increases, intercell interference (ICI) increases in the system that causing detrimental effects on SE, so precoders are designed to eliminate intercell SE. Using the MIMO systems reduces on-air latency, which is one of the new generations of wireless communications in heterogeneous environments. Another effective instrument in 5G communication is the use of mmWaves. The bandwidth of mmWaves a range from 30 to 300 GHz is considered an alternative band to compensate for the lack of bandwidth in the physical layer in generating this cellular communication. To ensure mmWave systems coverage, an ultradense network is introduced as a promising technology to achieve high system capacity [8]. Using this frequency band based on the nature of the mmWave band, causes the number of wave reflections in contact with objects to be significantly reduced and increases the number of base stations, thereby increasing the potential for intercell and intracell interference.

Moreover, massive MIMO array antennas are applied as one of the central promises of high directional beamforming to deal with path loss due to the mmWave signals seriously. Using massive MIMO because of small fading, intercell, and intracell interference can be significantly reduced by addressing the phenomenon of pilot signal contamination [9–16]. Using linear precoders in multicell and singlecell scenarios has demonstrated that the total achievable rate can increase significantly concerning the ratio of BS antennas to the user. In recent years, many studies have been done on designing and using hybrid precoders too.

Unfortunately, for the mmWave, MIMO systems run with many antennas, digital processing is not cost-effective because it incurs substantial costs for the system hardware, resulting in many complications. Hybrid precoder architecture is provided where the signal is processed by both analog and digital precoders to reduce cost and provide suitable performance [17–20]. Using a multiuser scenario, a hybrid precoder was examined by a greedy-like approach where a simultaneous orthogonal matching pursuit (SOMP) algorithm is proposed [19]. The methods mentioned above are based on the assumption of perfect channel state information and the availability of array response sets, i.e., F and W for precoder and combiner, respectively. These sets combine sending and receiving control vectors in the face of arrival/departure (DoA/DoD) where the users are stationed. In Alkhateeb et al., when a single RF chain is used in mobile phone users, the low-resolution analog-to-digital converters (ADCs) performance is examined, and in [21, 37], the nonconvex problem is solved by the inner-convex method. The findings have demonstrated that compared to traditional optimization techniques, l_0-norm relaxation techniques can significantly reduce interference compared to other techniques for eliminating cloud-radio access networks (C-RAN) interference. The authors [37] have presented a connected structure for a hybrid beamforming structure. An optimization problem is broken down into several subproblems consisting of precoder matrices with hybrid digital and analog precoders being created with an aggregate performance around near-optimal points through submatrices to precode each subarray. Hence, it seems to be a relatively tricky path in terms of complexity. In Chan et al. [22], it is shown that the Gram matrix of the frequency-selective channel can be broken down into frequency-flat and frequency-selective components as these components can be used in analog and base-band precoders. In Lin et al. [23], the channel matrix is broken down into an angular amplitude base matrix and a yield matrix, which fully correspond to the hybrid precoder structure. A hybrid precoding processor based on parallel-index-selection corresponding to matrix-inversion-free orthogonality has been proposed in the study by Lee et al. [24]. In Raghavan et al. [25], after directional precoded structures establish communications as a low-and high-complexity solution to meet data volume demand, a simple class of directional schedules based on channel structure is provided. Then, the performance between single- and multiuser scenarios is compared. In Ni and Dong [26, 38], for massive multiuser MIMO systems, a hybrid block diagonalization scheme has been suggested to approach the capacity performance of the base-band digital method. Generally, one would suggest many techniques that have been used to simplify the problem and create various hybrid precoder designs to create a suitable instrument to increase the SE. Castanheira et al [27] have tried to eliminate both inter/intratier interferences for uplink ultradense mmWave heterogeneous networks through the employment of low-feedback hybrid precoder-equalizer in the multicell massive MIMO systems. The analog part of the system has been optimized by minimizing the distance between the hybrid and the fully digital approaches [28]. Based on the dominance of interuser interference, intrauser interference, or both in downlink mmWave MIMO, nonlinear successive interference cancellation (SIC)-aided hybrid beamforming algorithms have been proposed with 2-bit finite resolution phase shifters that can achieve over 91% SE of infinite resolution phase shifters. Lavdas et al [29] presented an adaptive hybrid beamforming approach of the 5 G·mmWave cellular networks. The proposed scheme is the deployment of a separate RF chain connected per vertical antenna array, and a different set of antenna elements are active to perform radiation pattern formulation. Reducing total downlink transmission power due to hardware complexity reduction improves mmWave massive MIMO performance.

In this paper, we propose a multicell interference processing scheme for a hybrid precoder structure-based MIMO Broadcasting Channel. Inspired by the idea of signal subspace alignment and turning the basic equation into a convex equation to design a hybrid precoder, we reduce the signal-to-noise ratio (SNR) of each BS to reduce ICI with RF receivers and to develop a beamforming problem.

In Section 2, system model of our work is described in detail. We have the multicells, multiusers MIMO system whose rate is affected by intracellular interferences. Then, we define an optimization problem for precoding. In Section 3, we expose an WSMSE algorithm to solve the optimization problem because it is nonconcave in the precoding matrix. Using this method, two new matrices will be obtained to calculate the new precoder matrix. Another method to solve the optimization problem, KG precoder algorithm is exposed in Section 4. Because precoding optimization problem is highly nonconvergent. In the V-A section, DAV is used in the WSMSE and KG algorithms. Moreover, in the V-B section, we present a novel version of the WSMSE where the number of antennas is very large compared to the number of users named WSMSE, a New Form. All results are summarized in VI conclusions.

1.1. Notation. The following notation is adopted throughout the thesis: boldface upper symbols represent matrices and boldface lower symbols represent vectors. Scalars are denoted in lower case symbols. The transpose and conjugate transpose operators are denoted by $(.)^T$ and $(.)^H$, respectively. det(·), tr(·), and $(.)^{-1}$ denote the matrix determinant, trace, and inverse, respectively. E(·) denotes the expectation of a random variable. log(·) denotes the binary logarithm.

2. System Model

To eliminate interference and maximize SE, we consider the downlink multicell, multiuser MIMO scenario; in this scenario, there are C cells ($c = 1\sim C$), each of which includes a BS with M antenna (we consider isotropic); these antennas transmit data to K users who are equipped with N antennas in Rxs. The received signal $\boldsymbol{y}_{c,k} \in C^{N\times 1}$ in user k in cell c is expressed as follows:

$$\mathbf{y}_{c,k} = \sum_{m=1}^{C}\sum_{l=1}^{K}\mathbf{H}_{m.c,k}\mathbf{G}_{m,l}\mathbf{s}_{m,l} + \mathbf{n}_{c,k}. \tag{1}$$

In the above relation, user symbols are selected as Gaussian codebooks (i.e., $\mathbf{s}_{m,l} \in \mathbb{C}^{d_{m,l},1}$), each element of which $\sim N\mathbb{C}(0,1)$ is linearly precoded, generating the transmitted signal. $d_{m,\ l}$ is the number of sequences permitted by user l of cell m. $\mathbf{G}_{m,l,} \in \mathbb{C}^{M\times d_{m,l}}$ is the precoding vector of user l in cell m. $\mathbf{H}_{m.c,k} \in \mathbb{C}^{N\times M}$ is the channel matrix from the sender m to the user k of cell c. $\mathbf{n}_{c,k}$ of the next vector $\mathbb{C}^{N\times 1}$ involves independent mixed Gaussian noise expressions with mean zero and variance σ^2. Moreover, the covariance matrix of $\mathbf{H}_{i.c,k}$ channel is equal to $E[\mathbf{H}_{i,c,k}^H \mathbf{H}_{i,c,k}] = \Theta_{i,c,k}$. Because of the power budget constraint per Tx, the average power constraint is defined for the precoders. Thus,

$$tr\mathbf{G}_c\mathbf{G}_c^H \preccurlyeq P_c \; for \; c \in C, \tag{2}$$

where C is the set of all BSs. $\mathbf{G}_c = [\mathbf{G}_{c,1}, \mathbf{G}_{c,2}, \ldots, \mathbf{G}_{c,K}] \in \mathbb{C}^{M\times K}$ is the precoding matrix and P_c is the total transmitted power in cell c.

Assuming optimal singleuser coding and CSIT (Channel State Information at the Transmitter) and full CSI in the receivers of CSIR (Channel State Information at the Receiver), the achievable rate $r_{c,k}$ of user k of cell c is shown as follows:

$$\begin{aligned} r_{c,k} &= \log\det\left(\mathbf{I}_N + \Gamma_{c,k}\right), \\ \Gamma_{c,k} &= \mathbf{R}_{\widehat{c,k}}^{-1}\mathbf{H}_{c,c,k}\mathbf{Q}_{c,k}\mathbf{H}_{c,c,k}^H, \end{aligned} \tag{3}$$

where $\mathbf{Q}_{c,k} = \mathbf{G}_{c,k}\mathbf{G}_{c,k}^H$ is the transmission covariance matrix; $\boldsymbol{\Gamma}_{c,k}$ is the ratio of signal to interference along with the (SINR) noise of user k of cell c; and $\mathbf{R}_{\widehat{c,k}}^{-1}$ is the covariance matrix of the interference along with the noise received by user k of cell c, which is defined as follows:

$$\begin{aligned} \mathbf{R}_{c,k} &= \mathbf{H}_{c,c,k}\mathbf{Q}_{c,k}\mathbf{H}_{c,c,k}^H + \mathbf{R}_{\widehat{c,k}}, \\ \mathbf{R}_{\widehat{c,k}} &= \sum_{(j,i)\neq(c,k)} \mathbf{H}_{j,c,k}\mathbf{Q}_{j,i}\mathbf{H}_{j,c,k}^H + \sigma^2\mathbf{I}_N. \end{aligned} \tag{4}$$

This rate is strongly affected by intracellular interferences, especially when Rxs are placed at the cell's edge (Figure 1).

For example, the interference signals received in the DL may be very intense and even comparable to the signal strength for the user at the edge of the cell; this significantly reduces the achievable rate. To improve performance in cellular systems and maximize the weighted sum rate for all users, smart spatial signal processing techniques should be used in BSs and Rxs. Moreover, we consider the coordinated beam forming method, in which each BS sends data only to its users. However, the CSI is shared between the BSs for each BS to use more of its spatial dimensions to suppress interference generated in other cells (see Figure 2). Thus, we deal with an optimization problem, which is defined as follows:

$$\mathbf{G} = arg\max_{G} \sum_{c=1}^{C}\sum_{k=1}^{K} u_{c,k}k^T c,k, \tag{5}$$

where

$$s.t.tr\mathbf{G}_c\mathbf{G}_c^H \leq P_c \; for \; c \in C. \tag{6}$$

In the above relations, $\boldsymbol{G}$ is an abbreviation for $\{\mathbf{G}_c\}_{c\in C}$ and $u_{c,k} \geq 0$ is the weight of user k in cell c and is the issue utility function.

There are two algorithms to solve the above problem: the WSMSE algorithm and the KG algorithm; later, we describe them as follows.

3. WSMSE Algorithm

It is difficult to directly solve the optimization problem in (7) because it is extremely nonconcave in the G precoding matrix. To solve it, the linear filters of the receiver $\mathbf{F}_{c,k} \in \mathbb{C}^{N\times d_{c,k}}$, the error variance $\mathbf{E}_{c,k} \in \mathbb{C}^{d_{c,k}\times d_{c,k}}$ after linear filtering is received (given in (8)), and additional weighting matrices $\mathbf{W}_{c,k} \in \mathbb{C}^{d_{c,k}\times d_{c,k}}$ are considered to modify the utility function (7) and define the equation of optimization problem as follows [30]:

$$\begin{aligned} &\{\mathbf{G}, \mathbf{F}, \mathbf{W}\} = \\ &arg\min_{\mathbf{G},\mathbf{F},\mathbf{W}} \sum_{(c,k)} u_{c,k}\left(tr\left(\mathbf{W}_{c,k}\mathbf{E}_{c,k} - log\ de\ t\left(\mathbf{W}_{c,k}\right)\right)\right) \\ &s.t.tr\mathbf{G}_c\mathbf{G}_c^H \leq P_c \; for \; c \in C, \end{aligned} \tag{7}$$

along with

$$\mathbf{E}_{c,k} = E\left[\left(\mathbf{F}_{c,k}^H\mathbf{y}_{c,k} - \mathbf{s}_{c,k}\right)\left(\mathbf{F}_{c,k}^H\mathbf{y}_{c,k} - \mathbf{s}_{c,k}\right)^H\right]. \tag{8}$$

The above relation represents the mean squared error (MSE), i.e., the error variance in Rx. The advantage of defining the problem in this way is that the objective function is convex and depends on the second-degree G. We define $\rho_c = (P_c/\sigma^2)$ as the signal-to-noise ratio (SNR) in cell c. After using intermittent optimization techniques, the precoders are obtained from (8) as follows:

$$\mathbf{F}_{c,k} = \left(\sigma^2\mathbf{I}_N + \sum_{m=1}^{C}\sum_{l=1}^{K}\mathbf{H}_{m,c,k}\mathbf{G}_{m.l}\mathbf{G}_{m,l}^H\mathbf{H}_{m,c,k}^H\right)^{-1}\mathbf{H}_{c,c,k}\mathbf{G}_{c,k}, \tag{9}$$

$$\mathbf{W}_{c,k} = \left(\mathbf{I}_{d_{c,k}} - \mathbf{F}_{c,k}^H\mathbf{H}_{c,c,k}\mathbf{G}_{c,k}\right)^{-1}, \tag{10}$$

$$\mathbf{G}_{c,k} = \left(\sum_{J}^{C}\sum_{I}^{K} u_{j,i}\mathbf{H}_{c,j,i}^H\mathbf{D}_{j,i}\mathbf{H}_{c,j,i} + \lambda\mathbf{I}_M\right)^{-1}\mathbf{H}_{c,c,k}^H\mathbf{F}_{c,k}\mathbf{W}_{c,k}, \tag{11}$$

where $\mathbf{D}_{i,j} = \mathbf{F}_{i,j}\mathbf{W}_{i,j}\mathbf{F}_{i,j}$. Then, $\boldsymbol{F}_{c,k}$ and $\boldsymbol{W}_{c,k}$ are calculated; these two make new to $\mathbf{G}_{c,k}$ precedes. The Lagrangian λ_c must be adjusted by the bisection method to meet the power constraint conditions. However, if we disregard the bisector method, we can use Christensen et al. [31]; this reference provides a package term for Lagrange. Therefore, the work process is redefined as follows:

$$\mathbf{G}_{c,k} = \xi_c\left(\sum_{J}^{C}\sum_{I}^{K} u_{j,i}\mathbf{H}_{c,j,i}^H\mathbf{D}_{j,i}\mathbf{H}_{c,j,i} + \frac{tr\mathbf{D}_c}{M_{\rho c}}\mathbf{I}_M\right)^{-1}\mathbf{H}_{c,c,k}^H\mathbf{F}_{c,k}\mathbf{W}_{c,k}. \tag{12}$$

In (12), $\mathbf{W}_c = di\ ag(w_{c,1}, \ldots, w_{c,k})$, $\mathbf{A}_c = di\ ag(a_{c,1}, \ldots, a_{c,k})$, $\mathbf{D}_c = \mathbf{A}_c^H\mathbf{W}_c\mathbf{A}_c$, $\mathbf{A} = di\ ag(\mathbf{A}_1, \mathbf{A}_2, \ldots, \mathbf{A}_c)$, and

$\mathbf{D} = di\ ag(\mathbf{D}_1, \mathbf{D}, \ldots, \mathbf{D}_c)$, and ξ_c represents normalization and is defined as follows:

$$\xi_c^{(j)} = \sqrt{\frac{P_c}{\mathbf{G}_{c,k}\mathbf{G}_{c,k}^H}} = \sqrt{\frac{P_c}{\mathbf{\Psi}_c^{(j)}}}. \tag{13}$$

This process is repeated until it reaches the local optimum point.

4. KG Precoder Algorithm

Another method for solving the problem defined in (7) is to use the classical difference of the convex (DC) functions programming method described in the study by Kim and Giannakis [32, 36] and Al-Shatri and Weber [33]. The problem defined in (7) is due to the interference of a nonconvex problem. Therefore, in the KG algorithm, the desired signal is separated from a sum of rates of the remaining signals resulting in the problem being nonconvex. The rest of the signals are linearized using the Taylor expansion method because a linear function is both convex and concave. Put it simply, if we only consider the WSR dependence on $Q_{c,k}$, we can rewrite the objective function in (7) as follows:

$$\begin{aligned} WSR &= u_{c,k}\log\det\left(\mathbf{R}\frac{-1}{c,k}R_{c,k}\right) + WS\mathbf{R}\overline{c,k}, \\ WSR_{\widehat{c,k}} &= \sum_{(j,i)\neq(c,k)} u_{j,i}\log\det\left(\mathbf{R}\frac{-1}{j,i}\mathbf{R}_{j,i}\right). \end{aligned} \tag{14}$$

We consider first-degree Taylor series expansion in $\mathbf{Q}_{c,k}$ on $\widehat{\mathbf{Q}}$ *(i.e., all of* $\widehat{\mathbf{Q}}_{j,i}$) along with $\widehat{\mathbf{R}}_{j,i} = \mathbf{R}_{j,i}(\widehat{\mathbf{Q}})$; then,

$$WSR_{\widehat{c,k}}\left(\mathbf{Q}_{c,k},\widehat{\mathbf{Q}}\right) \approx WS\mathbf{R}_{\widehat{c,k}}\left(\widehat{\mathbf{Q}}_{c,k},\widehat{\mathbf{Q}}\right) - tr\left\{\left(\mathbf{Q}_{c,k} - \widehat{\mathbf{Q}}_{c,k}\right)\widehat{\mathbf{A}}_{c,k}\right\}, \tag{15}$$

with

$$\begin{aligned} \widehat{\mathbf{A}}_{c,k} &= \frac{\partial W\ S\mathbf{R}_{\widehat{c,k}}\left(\mathbf{Q}_{c,k},\widehat{\mathbf{Q}}\right)}{\partial \mathbf{Q}_{c,k}}\Big|_{\widehat{\mathbf{Q}}_{c,k},\widehat{\mathbf{Q}}} \\ &= \sum_{(j,i)\neq(c,k)} u_{j,i}\mathbf{H}_{c,j,i}^H\left(\widehat{\mathbf{R}}\frac{-1}{j,i} - \widehat{\mathbf{R}}_{j,i}^{-1}\right)\mathbf{H}_{c,j,i}. \end{aligned} \tag{16}$$

Note that the linearized expression for $WSR_{\widehat{c,k}}$ forms the lower limit for it. Now, setting aside the fixed expressions, we redefine the parameter $Q_{c,k} = G_{c,k}G_{c,k}^H$, to execute this linearization for all users, and complete the WSR cost function with constraint conditions; thus, we get Lagrangian as follows:

$$\begin{aligned} WSR(\mathbf{G},\widehat{\mathbf{G}},\lambda) = &\sum_{j=1}^{C}\lambda_c P_c + \sum_{c=1}^{C}\sum_{k=1}^{K} u_{c,k} log\,det\left(\mathbf{I}_{d_{c,k}} + \mathbf{G}_{c,k}^H\widehat{\mathbf{B}}_k\mathbf{G}_{c,k}\right) \\ &- tr\left\{\mathbf{G}_{c,k}^H\left(\widehat{\mathbf{A}}_{c,k} + \lambda_c\mathbf{I}_M\right)\mathbf{G}_{c,k}\right\}, \end{aligned} \tag{17}$$

where

$$\widehat{\mathbf{B}}_{c,k} = \mathbf{H}_{c,c,k}^H\widehat{\mathbf{R}}\frac{-1}{c,k}\mathbf{H}_{c,c,k}. \tag{18}$$

Indeed, the gradient of this convex low WSR bound (relative to $\boldsymbol{G}_{\mathrm{c,\,k}}$) is still the same as the gradient according to the original WSR criteria. This allows us to consider it as a general condition of the eigenmatrix; thus, $\mathbf{G}'_{c,k} = eigenmatrix(\widehat{\mathbf{B}}_{c,k}, \widehat{\mathbf{A}}_{c,k} + \lambda_c\mathbf{I}_M)$ is the generally normalized eigenmatrix of the above two matrices with eigenvalues $\sum_{c,k} = eigenmatrix(\widehat{\mathbf{B}}_{c,k}, \widehat{\mathbf{A}}_{c,k} + \lambda_c\mathbf{I}_M)$. The Lagrangian coefficients λ_c for all c are adjusted to meet the power limits $\sum_{k,l}\mathbf{P}_{c,k}(l,l) = P_c$. This can be done by performing the bisector method for each BS. Note that some Lagrangian coefficients may be zero. Assume $\sum_{c,k}^{(1)}\mathbf{G}'^H_{c,k}\widehat{\mathbf{B}}_{c,k}\mathbf{G}'_{c,k}$ and $\sum_{c,k}^{(2)} = \mathbf{G}'^h_{c,k}\widehat{\mathbf{A}}_{c,k}$ $G'_{c,k}$. The advantage of using (16) is that this equation allows direct power adaptation: by defining $\mathbf{P}_{c,k} \geq 0$ and substituting $\mathbf{G}_{c,k} = \mathbf{P}_{c,k}^{1/2}\mathbf{G}'_{c,k}$ in (16), we get

$$\begin{aligned} WSR = \sum_c \lambda_c P_c + \sum_{c,k}^{K}\Bigg\{ &u_{c,k} log\ de\ t\left(\mathbf{I}_{d_{c,k}} + \mathbf{P}_{c,k}\sum\nolimits_{c,k}^{(1)}\right) \\ &- tr\left(\mathbf{P}_{c,k} + \left(\sum\nolimits_{c,k}^{(2)} + \lambda_c\mathbf{I}\right)\right)\Bigg\}. \end{aligned} \tag{19}$$

This leads to water-filling with the knowledge of the following leakage:

$$\mathbf{P}_{c,k}(\mathrm{l},\mathrm{l}) = \left(\frac{1}{\sum_{c,k}^{(1)}(l,l)}\left(\frac{u_k}{\sum_{c,k}^{(2)}(l,l) + \lambda_c} - 1\right)\right)^+, \tag{20}$$

where for all l, we must have $\sum_{c,k}^{(1)} \geq 0$ (for all l s.t $\sum_{c,k}^{(1)} \geq 0$) where $z^+ = max(0, z)$. Moreover, note that as with any intermittent optimization process (here too), there are many updates with different effects on convergence speed. The variables that need to be updated are $\mathbf{G}'_{c,k}$, $\mathbf{P}_{c,k}$, and λ_c. The advantage of the DC method is that it works by using more or less specific values for many streams/user $d_{c,k}$ sequences. In other words, we can use the maximum number of eigenvalues $d_{c,k}^{max}$ of the eigenmatrix $\mathbf{G}'_{c,k}$. Maximum eigenvalues are eigenvectors corresponding to the most considerable eigenvalues. The water-filling method automatically (in each iteration) determines how many stream sequences to maintain.

5. Deterministic Annealing Variant (DAV) and WSMSE-New

5.1. DAV. According to Negro et al. [34], one finds that the maximization problem in (7) is highly nonconvergent. At low SNRs (high noise variance), any interference is negligible compared to noise. Thus, all links can be considered decoupled. Therefore, rate maximization, like singleuser MIMO, becomes SNR maximization for the sequence to which total power is allocated. Optimal Tx and Rx filters are the left and single right vectors that correspond to the most considerable single channel value between Tx and Rx. This means that for SNR = 0, convergences to the global optimum are guaranteed.

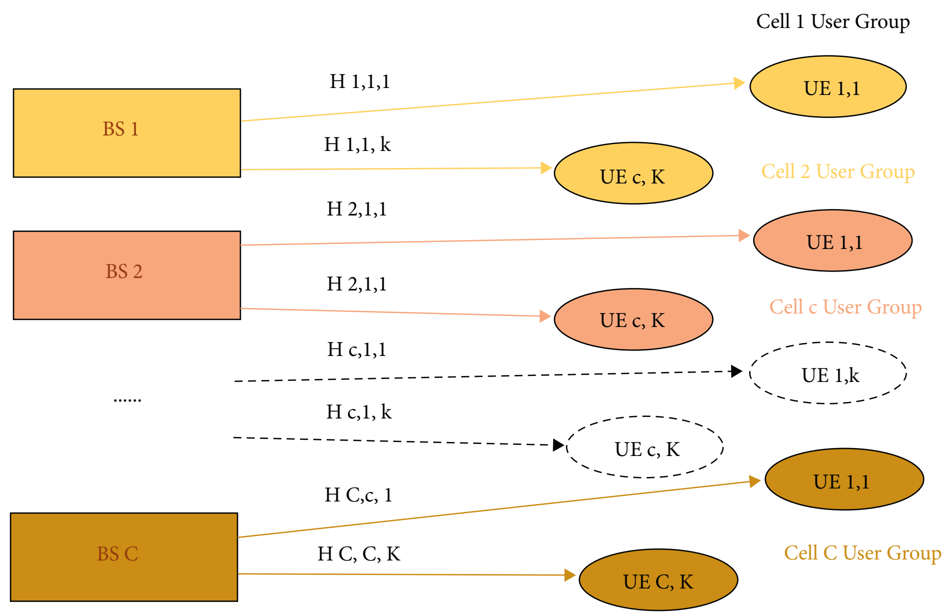

Figure 1: Interference broadcast channels or multicells, multiusers interference system model.

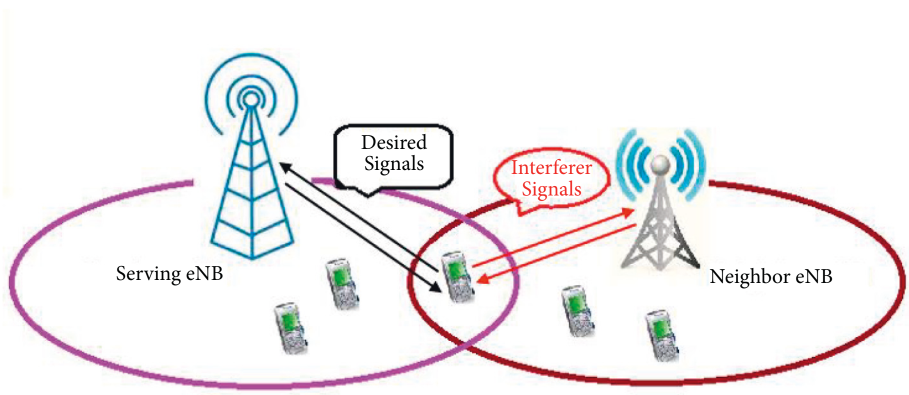

Figure 2: Intracell interference at the cell edges.

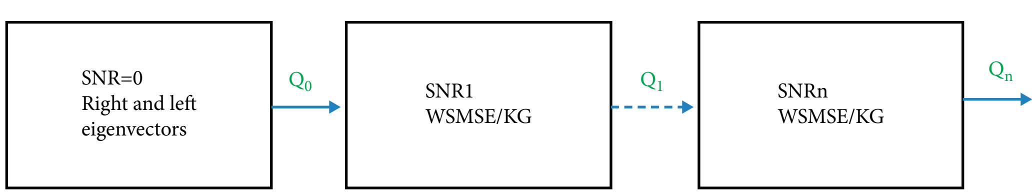

Figure 3: Deterministic annealing variant method.

Simultaneously, there are many more local optimum points because of the formation of additional sequences as soon as the SNR increases. Thus, as the SNR increases further, more local optimum sequences and points emerge. The idea of DAV (Figure 3) is to start the WSMSE (KG) with the response of the WSMSE (KG) algorithm at lower SNRs (starting from very low SNRs) that ensure convergence to the global optimum. This process goes on until a sequence distribution at higher SNRs is obtained that corresponds to the maximum sequence distribution for which the interference alignment is possible. Indeed, Tx and Rx filters reach the global response at very high SNRs.

To demonstrate the efficiency of the DAV method, we plot the total rate in terms of SNR for the IBC (Interference Broadcast Channels) system, for which the signals are pre-encoded by the WSMSE (KG) precursor and by the WSMSE (KG) precursor with the DAV. The last case means that the precursors at low SNR act as the trigger conditions for the precursor algorithm at high SNR. The classic WSMSE precoder is set up by eigenvectors to the right of the user

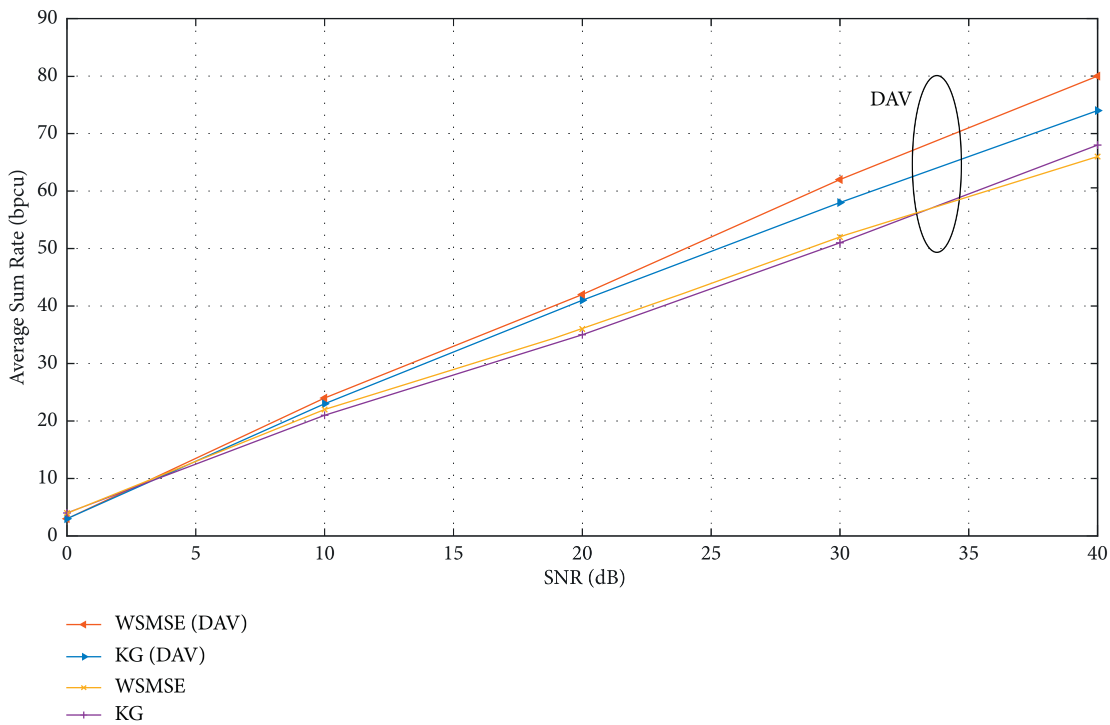

Figure 4: WSR in terms of SNR: $C = 5$, $K = 6$, $M = 5$, and $N = 5$.

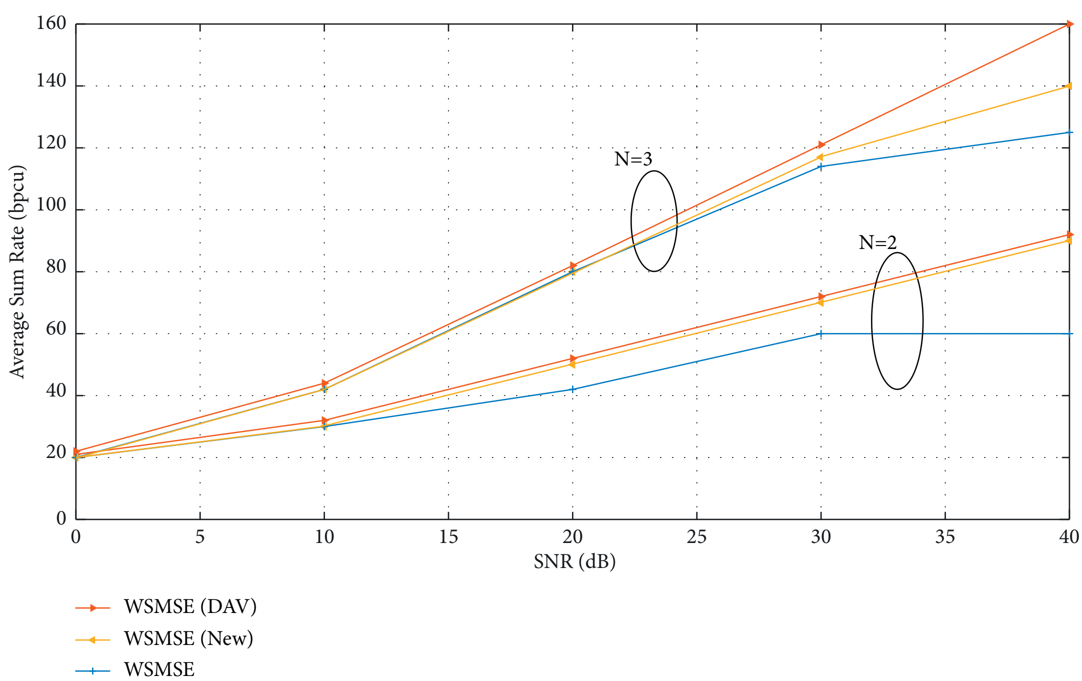

Figure 5: WSR in terms of SNR for $C = 5$, $K = 8$, $M = 15$, and $N = \{2, 3\}$.

channel. The classic KG is driven by zero matrices. The total number of iterations remains the same.

In other words, in using DAV, the number of iterations equals the total number of iterations needed to converge in each SNR used before the target SNR is reached. However, if we use classical algorithms, we will not need to iterate low SNRs, and we can run the algorithm immediately on the target SNR. Here, we will need some iterations equal to the total number of iterations if using DA. Figure 4 shows that DAV enhances the performance of the WSMSE and KG algorithms drastically.

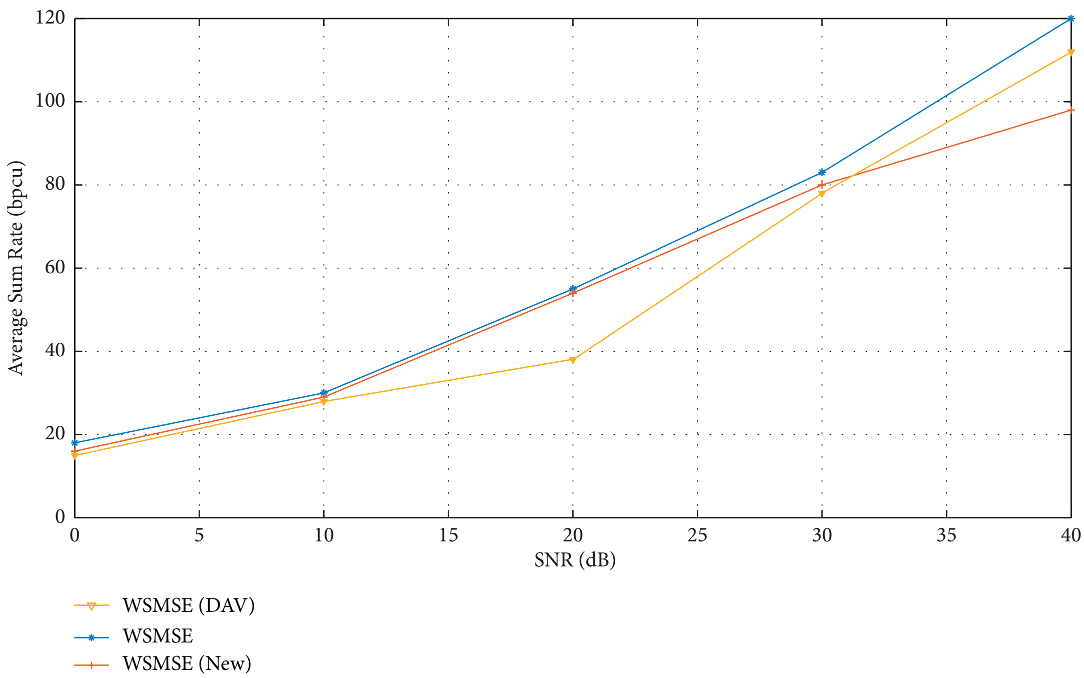

Figure 6: WSR in terms of SNR: $C = 3$, $K = 4$, $M = 10$, and $N = 2$.

Table 1: Simulation parameters and results of Figure 5.

$C = 5$	$K = 8$	$M = 15$	$N = 2$	$C = 5$ $K = 8$	$M = 15$	$N = 3$
SNR (dB)		WSR (bpcu)			WSR (bpcu)	
	New WSMSE	WSMSE	New WSMSE	New WSMSE	WSMSE	New WSMSE
0	20	20	20	20	20	20
5	26	26	26	32	32	32
10	37	37	37	45	45	45
15	42	39	42	62	62	62
20	53	42	53	80	42	80
25	62	50	62	99	97	100
30	76	60	76	117	115	120
35	82	60	82	129	120	140
40	92	60	92	139	125	158

5.2. WSMSE: A New Form. In this section, we present a novel version of WSMSE where the number of antennas is very large compared to the number of users; instead of Rx, MMSE (Minimum Mean Square Error), we use Rx matching filter (MF) as Rx user in detection (1). By using MF for DL detection in users, when the number of antennas at the BS is greater than the number of users, interuser interference will be suppressed [35]. Thus, in this case, we are no longer required to exchange the interference received by each user, and the Rx equation (10) becomes the following equation:

$$\mathbf{F}_{c,k} = \left(\sigma^2 \mathbf{I}_N + \mathbf{H}_{c,c,k} \mathbf{G}_{c,k} \mathbf{G}_{c,kl}^H \mathbf{H}_{c,c,k}^H\right)^{-1} \mathbf{H}_{c,c,k} \mathbf{G}_{c,k}. \quad (21)$$

This new developer can be named a WSMSE technique. This precoder's operation is as follows: Tx and Rx work together to eliminate incoming interference from sending to other users. If the number of Tx antennas is huge, Tx itself can eliminate the interference, and the complex Rx of the user is not required. Therefore, simple Rx techniques are optimized here.

The interesting point is that the new WSMSE precoder with a large number of Tx and simple Rx almost always achieves better local optimization points compared to the classical WSMSE precoder. The explanation is simple. If we use a simple Rx, the overlap will no longer create a link between Tx and Rx. This simplifies convergence. This does not affect performance as already stated since we have enough antennas in Tx to eliminate interference.

Figures 5 and 6 show the performance of the new WSMSE between the WSMSE and the WSMSE with the DAV, as the new WSMSE calls for fewer data to be exchanged and therefore achieves a better local optimum than the WSMSE. However, unlike WSMSE-DAV, it still cannot reach the global optimum. It has to be noted that, as shown in Figures 5 and 6, the method could only be used when the

TABLE 2: Simulation parameters and results of Figure 6.

$C = 3$	$K = 4$	$M = 10$	$N = 2$
SNR (dB)	WSR (bpcu)		
	New WSMSE	WSMSE	WSMSE (DAV)
0	17	17	17
5	20	22	22
10	22	35	35
15	26	44	44
20	39	59	59
25	58	69	72
30	80	80	89
35	97	87	103
40	112	97	118

number of Tx antennas is not less than the total number of receiving antennas of all users.

In sum,

(i) WSMSE with DAV is the extended version of WSMSE that uses DAV in the WSMSE precoder. Unlike WSMSE, which reaches the local optimum, this method achieves the global optimum.

(ii) The new WSMSE is a version of WSMSE where MF Rx replaces MMSE Rx. This method reaches better optimums than WSMSE and has a more straightforward Rx advantage. Thus, it requires less information exchange. Nonetheless, this method could only be used for many transmitter antennas.

(iii) The new WSMSE method is useful for analyzing large systems in MIMO single-string mode.

6. Conclusion

The results and parameters of our simulation are exposed in Tables 1 and 2.

In this section, we define the central problem, which is designing of precoders that maximize the weighted total rate for multicell scenarios under the condition of maximum power budget per cell. This rate is strongly affected by intracellular interference. We suggest using CBF. In CBF, all BSs exchange channel knowledge for the joint design of all BFs in the network. The problem is defined as the WSR maximization problem. If the ratio of the number of users served per cell is small enough to the number of transmitter antennas (approximately 1.10), simple linear beamformers like MF reaches great performance. In general cases, the two algorithms reach the best performance in terms of the total achievable rate. These two algorithms are WSMSE and KG. In the WSMSE algorithm, the problem of maximizing the total rate is solved by redefining it as the problem of minimizing the MSE function. The answer to this problem is obtained through an iterative algorithm. In this algorithm, we calculate $\boldsymbol{F}$, $\boldsymbol{W}$, and $\boldsymbol{G}$ alternately in each iteration. It has to be noted that $\boldsymbol{F}$ is for the filter on the Rx side, $\boldsymbol{W}$ is for the weight, and $\boldsymbol{G}$ is for the beam shaper. In the KG method, it is suggested that the objective function of the total rate should be divided into two functions, one function for the desired user rate *(c, k)* and the other function related to the total rate of the remaining users. These two functions are convex in $\boldsymbol{Q}_{c,k}$ (transmitter covariance) and nonconvex in $\boldsymbol{Q}_{c,k}$, respectively. It was suggested that the nonlinear part should be linearized to obtain a new objective function. This new function is the difference between a convex function and a linear function (a function that is both concave and convex). The answer to this new problem is obtained through the eigenmatrix of two matrices. This response is normalized; thus, the power must be adjusted. It is suggested that this be done using the water-filling approach. The WSMSE and KG both reach the local optimums. To force them to converge in global optimums, we must use the DAV method. Moreover, we suggest using the new WSMSE beam modulator. The new WSMSE is a version of the WSMSE algorithm obtained by substituting the $\mathbf{F}$ expression with the expression of MF in the MMSE. This beam generator is less complex compared to the WSMSE.

Advantages of the new WSMSE method are as follows:

(i) The new WSMSE calls for fewer data to be exchanged and, on the other hand, requires less information exchange

(ii) This method achieves better local optimums than the WSMSE

(iii) The new WSMSE method is useful for analyzing large systems in MIMO single-string mode

(iv) It is less complex compared to traditional WSMSE

Data Availability

Data are available. It will be shared at the request of the esteemed editor.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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